An Efficient and Robust Social Network De-anonymization Attack

Joint work with B. Simon, S. Imre

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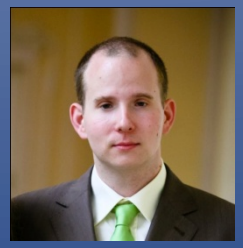
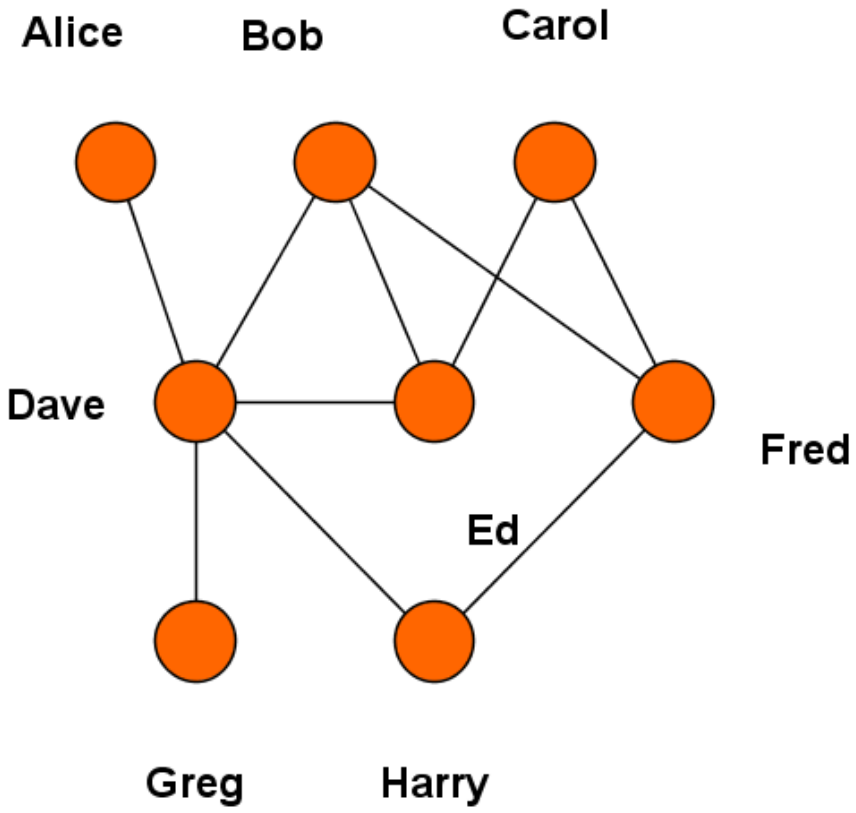


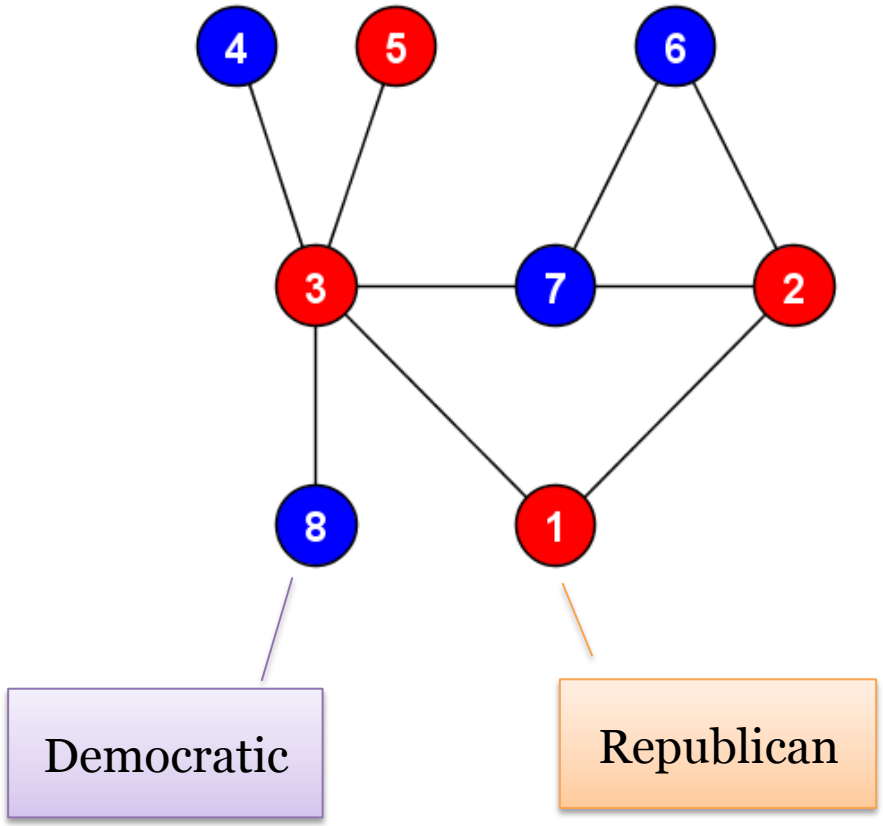
INVENTEURS DU MONDE NUMÉRIQUE

Re-identification using the structure

Auxiliary information, G_{src}
(a public crawl, e.g., Flickr)



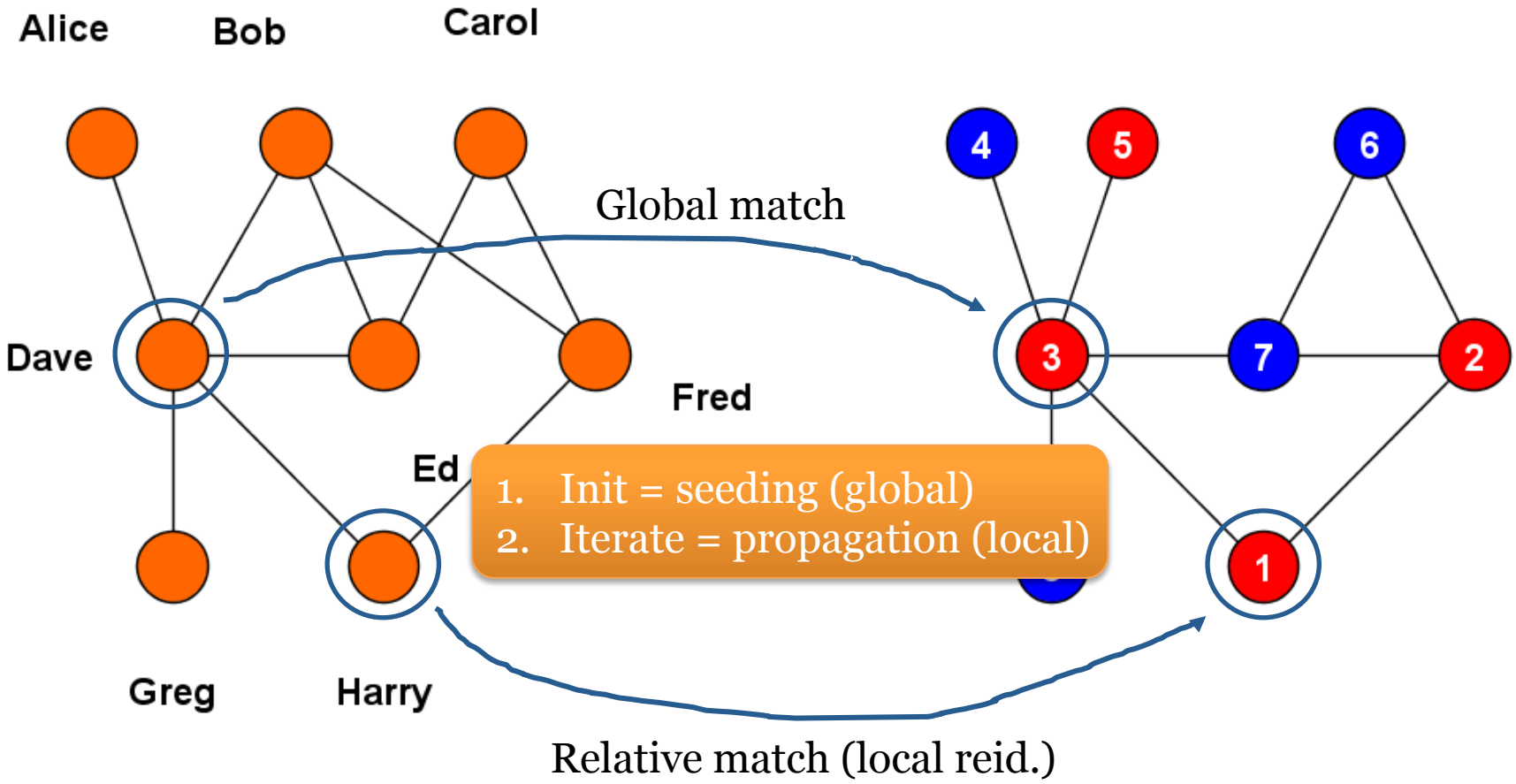
Anonimized graph, G_{tar}
(anonimized export, e.g., Twitter)



Re-identification using the structure (2)

Auxiliary information, G_{src}
(a public crawl, e.g., Flickr)

Anonimized graph, G_{tar}
(anonimized export, e.g., Twitter)



Narayanan&Shmatikov results (Nar09)

- Large social networks
  - Background knowledge: Flickr (3,3
  - An
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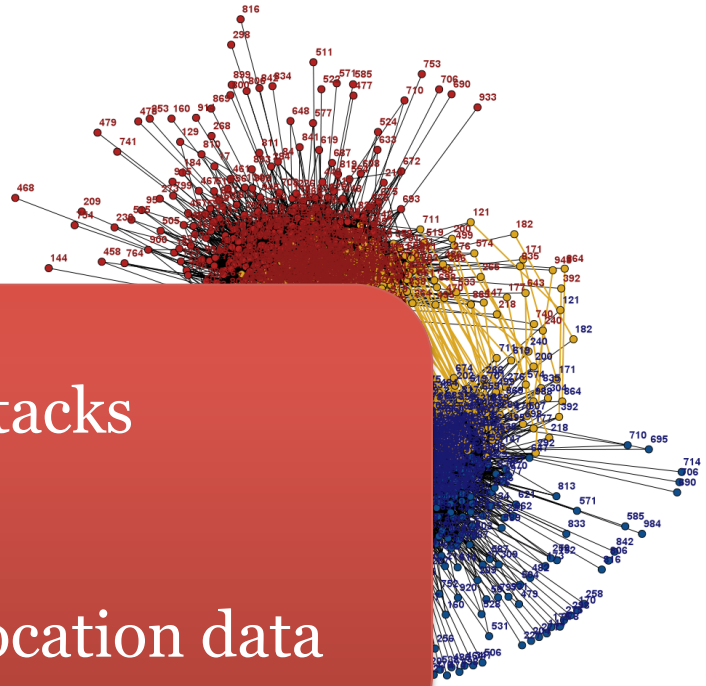
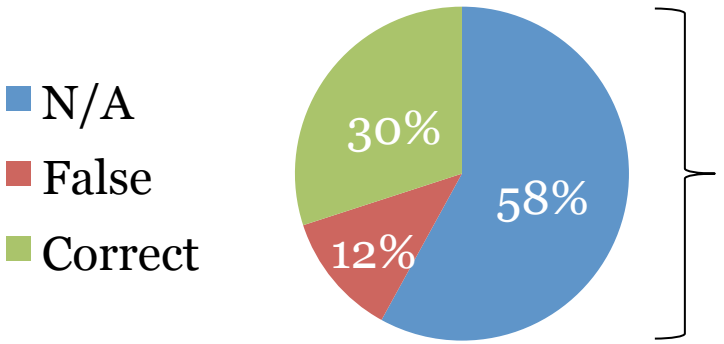
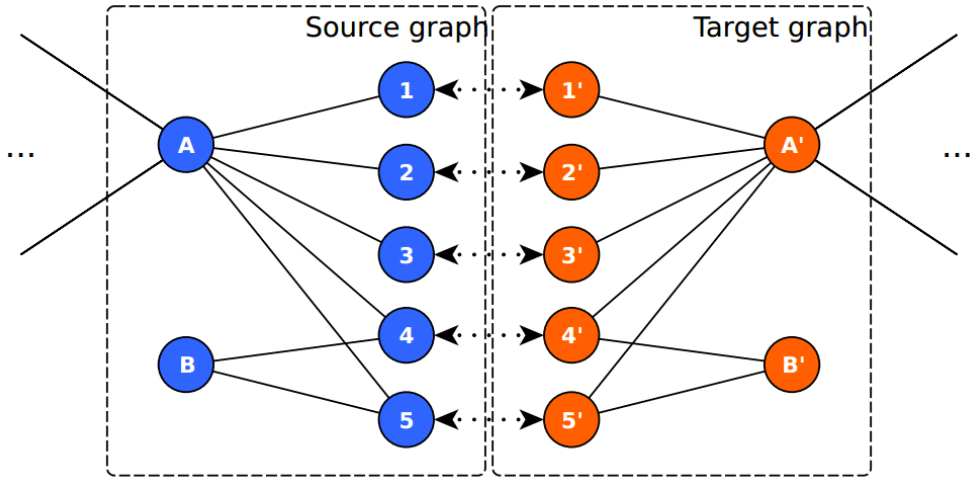


- De-anonymization attacks
- Linking attacks
- Re-identification of location data



Ground truth of 27k nodes
(verified by name/user/loc.)

Motivation for Bumblebee



$$\mathrm{NarSim}(v_i, v_j) = \frac{\#\mathrm{mutual\_nbrs}}{\sqrt{\deg(v_j)}}$$

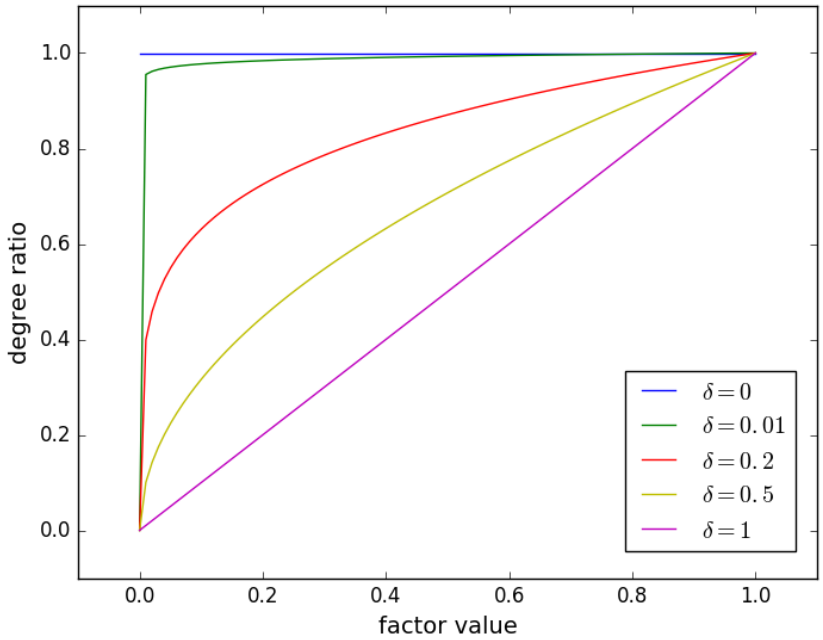
$$\mathrm{BlbSim}(v_i, v_j) = \#\mathrm{mutual\_nbrs} \cdot \left(\min\left(\frac{\deg(v_i)}{\deg(v_j)}, \frac{\deg(v_j)}{\deg(v_i)} \right) \right)^{\delta}$$

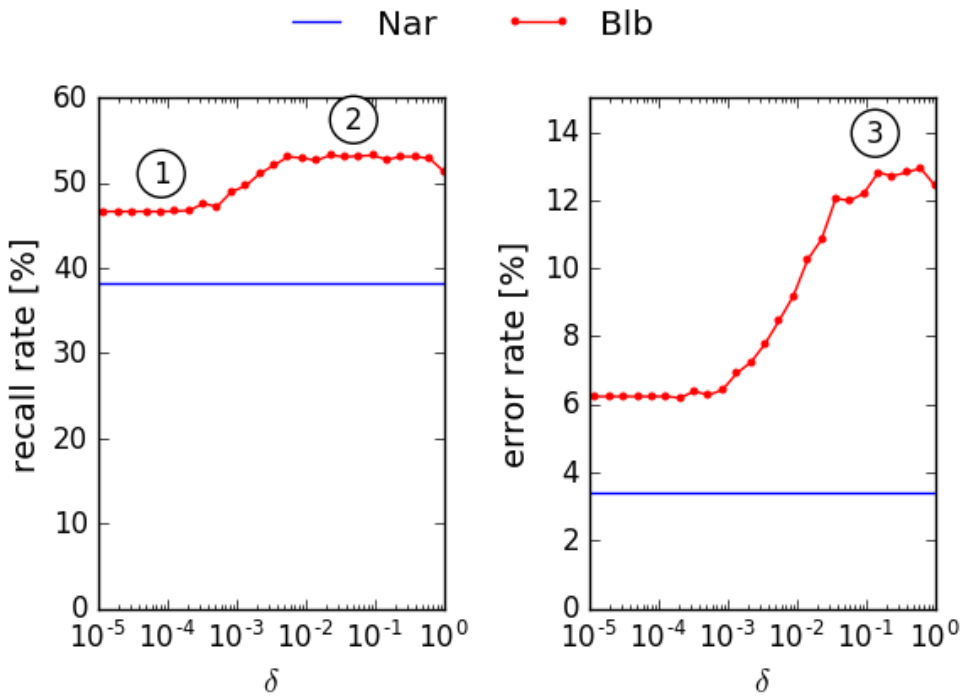
	A'	B'	?
A	$\frac{5}{\sqrt{100}}$	$\frac{2}{\sqrt{2}}$	B'
B	$\frac{2}{\sqrt{100}}$	$\frac{2}{\sqrt{2}}$	B'

	A'	B'	?
A	5	0.89	A'
B	0.89	2	B'

Parameters of the attack – δ

$$\mathrm{BlbSim}(v_i, v_j) = \#\mathrm{mutual\_nbrs} \cdot \left(\min\left(\frac{\deg(v_i)}{\deg(v_j)}, \frac{\deg(v_j)}{\deg(v_i)} \right) \right)^{\delta}$$





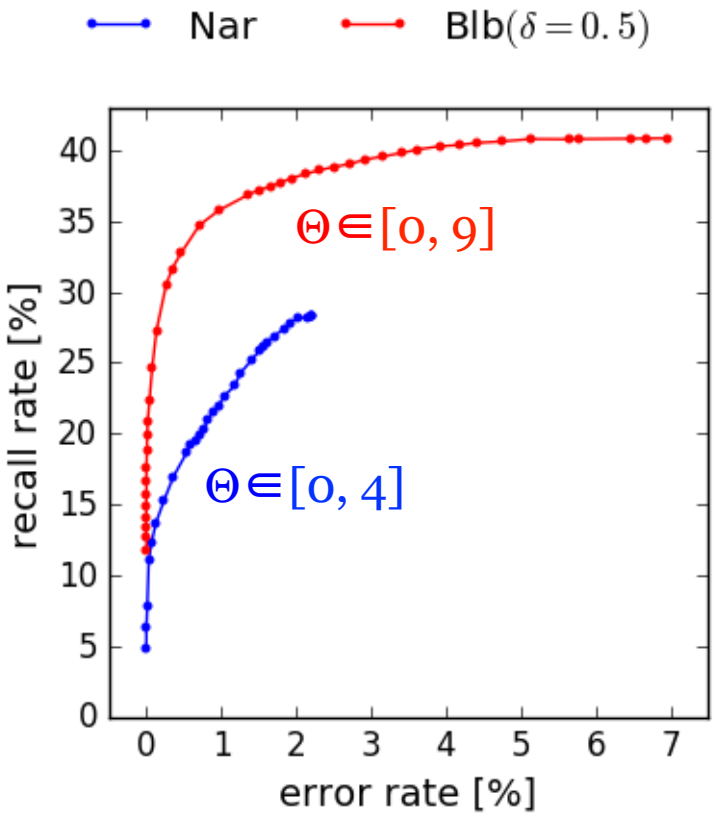
Visual playground: https://gulyas.info/snda

Parameters of the attack (2) – Θ

Algorithm 1: PROPAGATE

Data: G_{src}, G_{tar}, μ
Result: μ, Δ

$\Delta \leftarrow 0$;
for $v_{src} \in V_{src}$ **do**
  $S \leftarrow \text{SCORE}(G_{src}, G_{tar}, v_{src}, \mu)$;
  if $\text{ECC}(S.\text{VALUES}()) < \Theta$ **then**
    CONTINUE;
  end
  $v_c \leftarrow \text{RANDOM}(\text{MAX}(S))$;
  $S_r \leftarrow \text{SCORE}(G_{tar}, G_{src}, v_c, \mu^{-1})$;
  if $\text{ECC}(S_r.\text{VALUES}()) < \Theta$ **then**
    CONTINUE;
  end
  $v_{rc} \leftarrow \text{RANDOM}(\text{MAX}(S_r))$;
  if $v_{src} = v_{rc}$ **then**
    $\mu[v_{src}] \leftarrow v_c$;
    $\Delta \leftarrow \Delta + 1$;
  end
end



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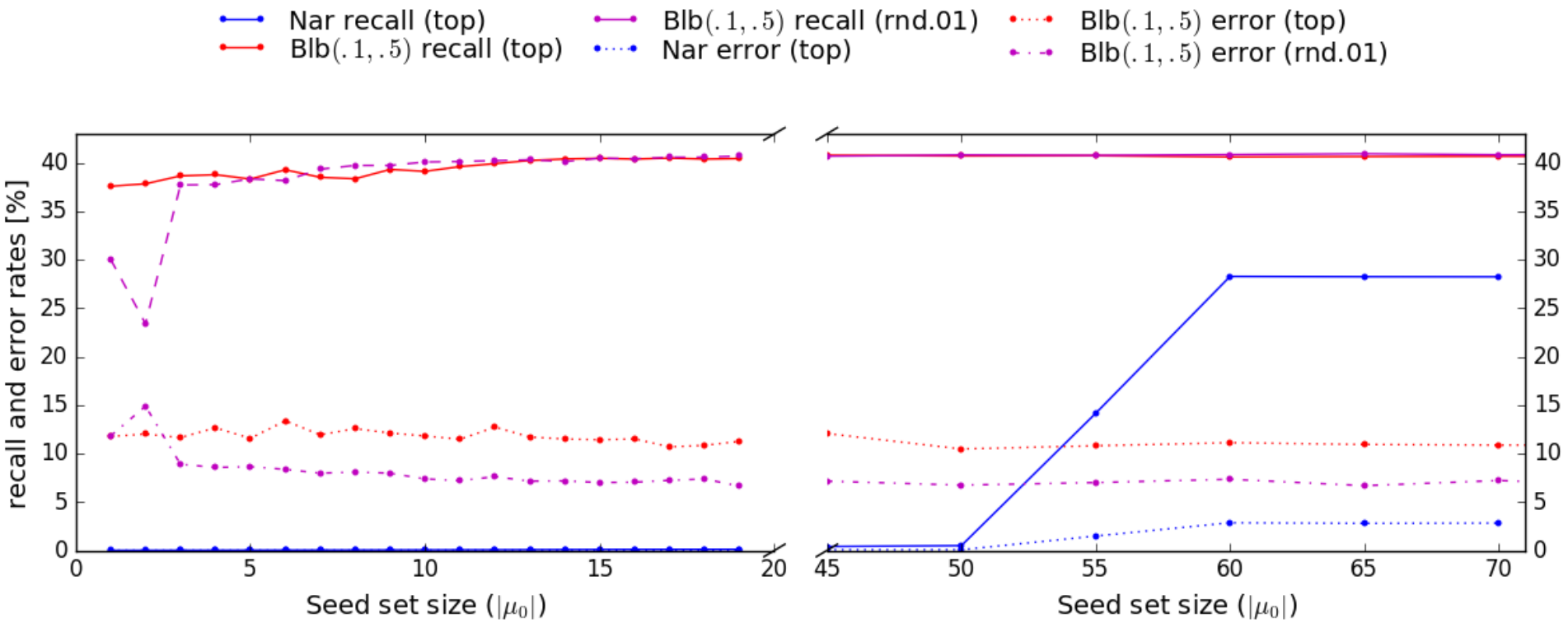
Seeding sensitvity



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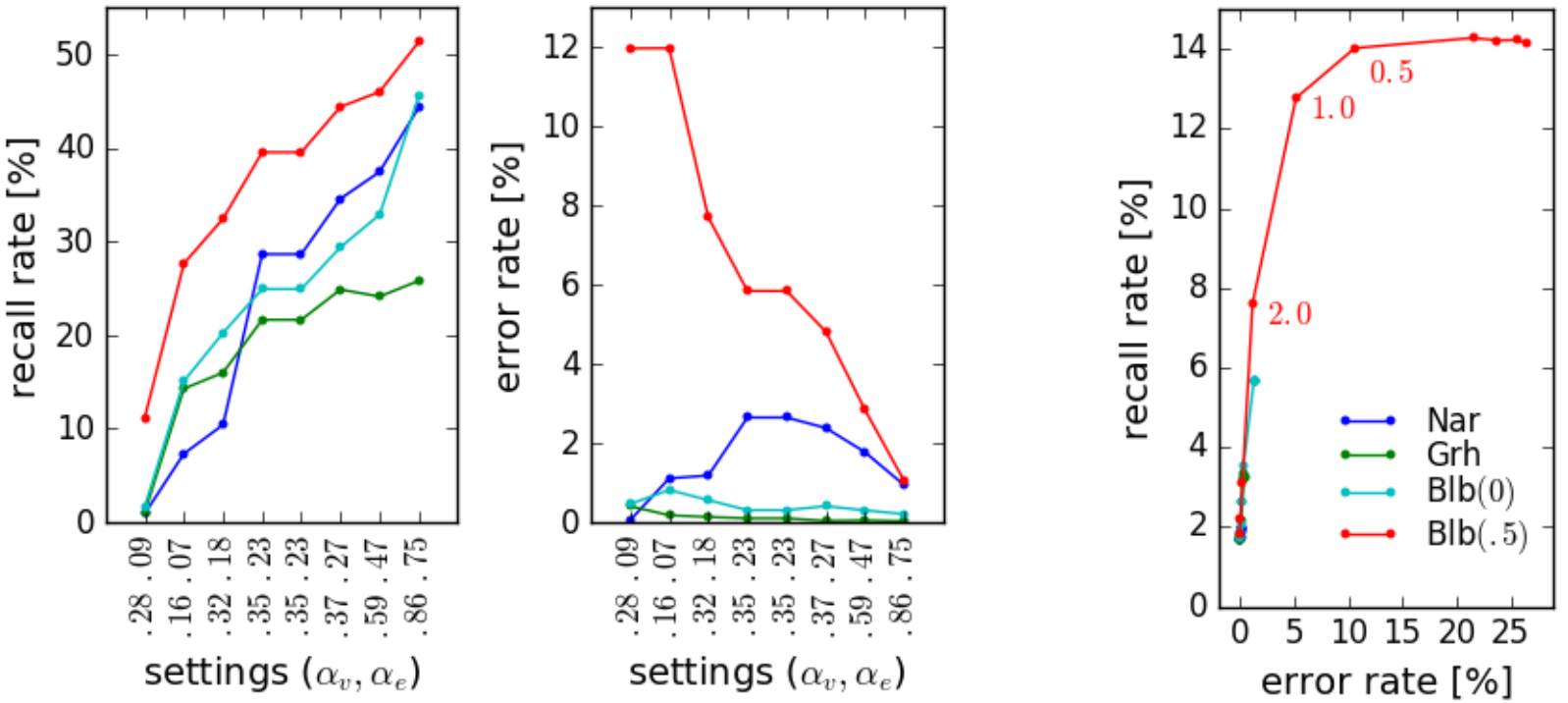
Robustness to noise



Visual playground: https://gulyas.info/snda

Comparison with other attacks

SecGraph: A Uniform and Open-source Evaluation System for Graph Data Anonymization and De-anonymization

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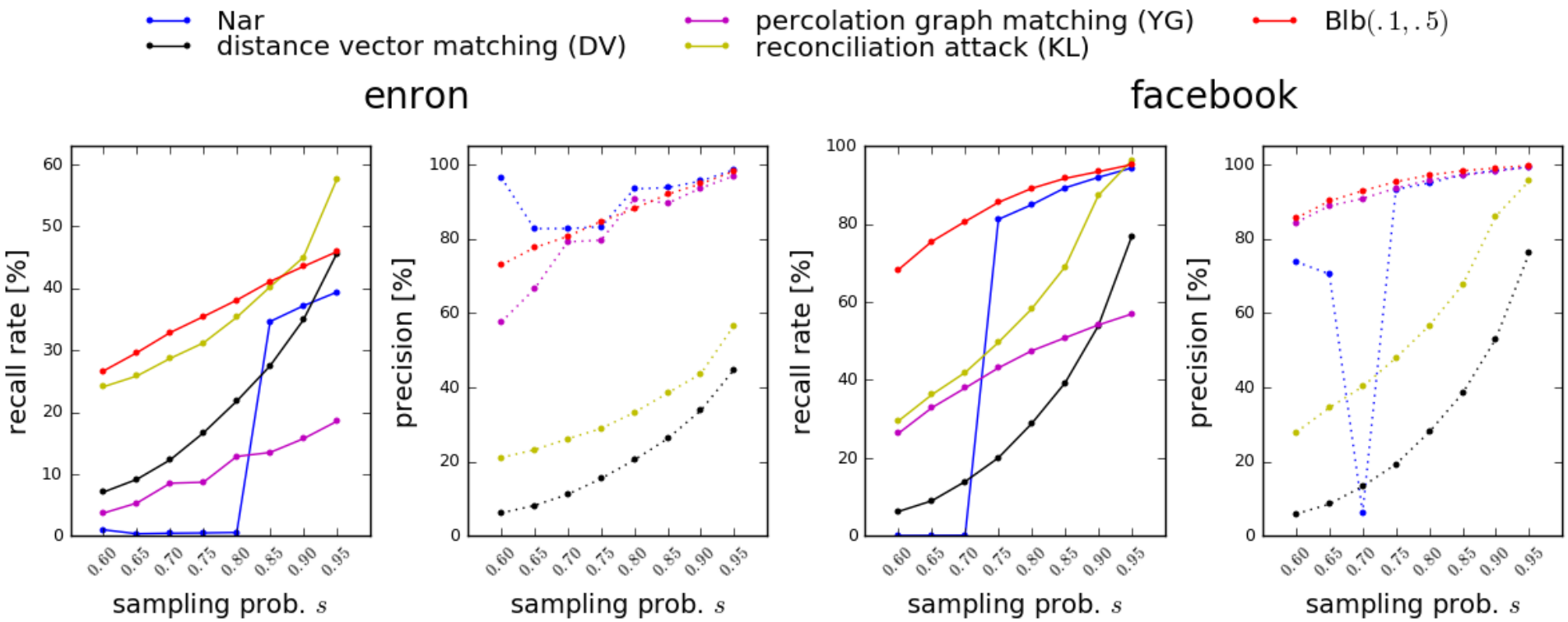
Abstract

In this paper, we analyze and systematize the state-of-the-art graph data privacy and utility techniques. Specifically, we propose and develop *SecGraph* (available at [1]), a uniform and open-source Secure Graph data sharing/publishing system. In SecGraph, we systematically study, implement, and evaluate 11 graph data anonymization algorithms, 19 data utility metrics, and 15 modern Structure-based De-Anonymization (SDA) attacks. To the best of our knowledge, SecGraph is the first such system that enables data owners to anonymize data by state-of-the-art anonymization techniques, measure the data's utility, and evaluate the data's vulnerability against modern De-Anonymization (DA) attacks. In

called *graph data*. For research purposes, data and network mining tasks, and commercial applications, these graph data are often transferred, shared, and/or provided to the public, research community, and/or commercial partners. Since graph data carry a lot of sensitive private information of users/systems who generated them [2, 3], it is critical to protect users' privacy during the data transferring, sharing, and/or publishing.

To protect users' privacy, several anonymization techniques have been proposed to anonymize graph data, which can be classified into six categorizes: Naive ID Removal, Edge Editing (EE) based techniques [6], *k*-anonymity based techniques [7–11], Aggregation/Class/Cluster based techniques [12–14], Differen-

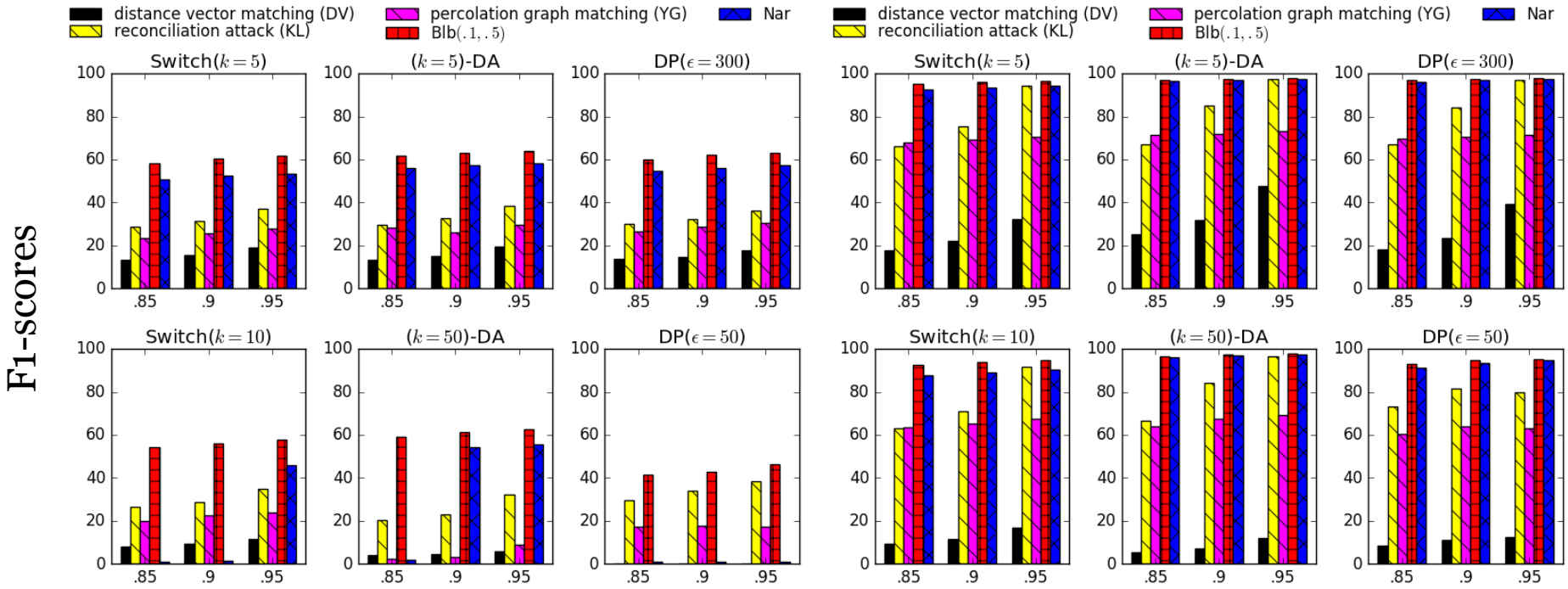
Comparison with other attacks (2)



Comparison with other attacks (3)

Enron (36k)

Facebook (63k)



$$\mathrm{F1} = 2 \cdot \frac{\mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$$

Conclusion

- We proposed a new attack based on a new scoring scheme, and showed its superiority to all existing attacks.

- Visual playground & Python code:

  https://gulyas.info/snda

- Seriously interested? Try out SALab, our framework for social network de-anonymization:

  https://github.com/gaborgulyas/salab

Thank you for your attention!

ANY QUESTIONS?

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